Application of an advanced statistical post-processing method using information from climate indices in calibration of seasonal precipitation forecasts in Java (Indonesia)

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INTRODUCTION

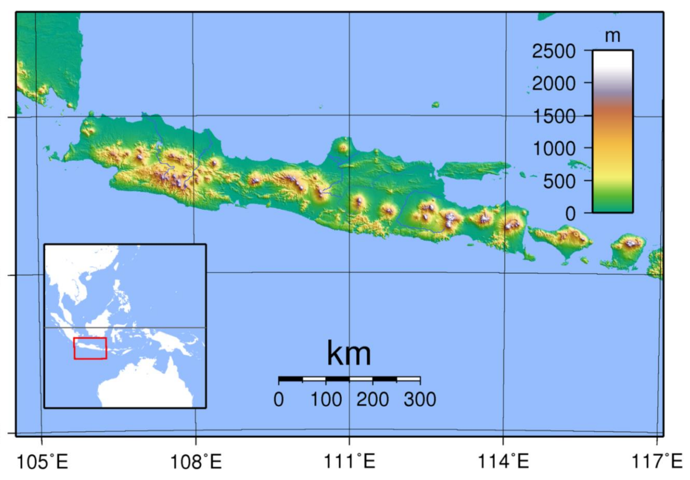

Figure 1 : Java as the study area (source: wikipedia.org/wiki/Java).

In this study we explore the added value of an advanced statistical post-processing method, *Logistic Distribution Fitting*, to improve probabilistic precipitation forecasts from the ECMWF Seasonal Forecast System 5 (ECMWF-SEAS5), compared to the empirical quantile mapping (EQM) that has been previously applied by Ratri et al (2019). It is expected that the skill of the ECMWF-SEAS5 precipitation forecasts in capturing extreme events, such as those occurring during El Nino and La Nina years, could be improved by statistical post-processing. Our study area is Java, Indonesia (Fig 1).

DATA AND METHOD

Table 1 : Potential predictor sets .

Predictor set	Based	Location (μ)	Scale (σ)
a. CRCH (Raw ECMWF based P): Mu=P+N.34(obs)+DMI (Obs)|| Sigma=P(mean,sd	Raw SEAS5	• Ensemble mean of SEAS5 Precipitation • Observed Niño3.4 index (month before analysis) • Observed Dipole Mode Index (DMI)	Ensemble mean and standard deviation of SEAS 5 precipitation
b. CRCH (EQM based P): Mu=P+N3.4(Obs)+DMI (Obs) || Sig=P(mean,sd)		• Ensemble mean of EQM Precipitation • Observed Niño3.4 index observation (month before analysis)	Ensemble mean and standard deviation of EQM precipitation

c. CRCH (EQM based P): Mu=P+N3.4(Mod)+DMI || Sig=P(mean,sd)	EQM	• Ensemble mean
		  • EQM Precipitation
		  • Forecast Niño3.4 index (from the month before the valid month)
		• Observed DMI
			Ensemble mean and standard deviation of EQM precipitation

d. CRCH (EQM based P): Mu=allpreds || Sig=allpreds		• Ensemble mean
		  • EQM Precipitation
		  • Forecast Niño3.4 (from the same month and the month before the valid month)
		• Observed Niño3.4 index (month before analysis)
		• Topography
		• Observed SST around Java island
		• Observed Madden-Julian Oscillation (MJO)
		• Observed DMI
			• Ensemble mean
			  • EQM Precipitation
			  • Forecast Niño3.4 (from the same month and the month before the valid month)
			• Observed Niño3.4 index (month before analysis)
			• Topography
			• Observed SST around Java island
			• Observed Madden-Julian Oscillation (MJO)
			• Observed DMI

The ECMWF-SEAS5 reforecasts that we use are for the period of 1981-2010. This seasonal forecast system runs for a 7-month lead time, with 25 ensemble members on a 35 km horizontal grid. As an observational data set we use SA-OBS (Van den Besselaar et al, 2017). Standardization and pooling the raw as well as the EQM-corrected SEAS5 monthly precipitation data are implemented before post-processing.

In this study, we used logistic distribution (Stauffer et al, 2017) with stepwise fitting using the Censored Regression with Conditional Heteroscedasticity (crch) package of R. In each step, a variable is considered for addition from 1 of the 4 set of variables (Table 1) based on the Akaike information criterion (AIC). The lower AIC is the better. We use a leave-three-years-out cross-validation technique to estimate the forecast skill using the continuous ranked probability skill score (CRPSS). Several experiments have been done such as comparing raw ECMWF SEAS5 Vs EQM-corrected precipitation as the base input, applying all potential predictors Vs 3 most selected based on the objective predictor selection, and Nino 3.4 index based on the observation data Vs Nino 3.4 index based on the forecast data.

VERIFICATION OF SEASONAL FORECASTS

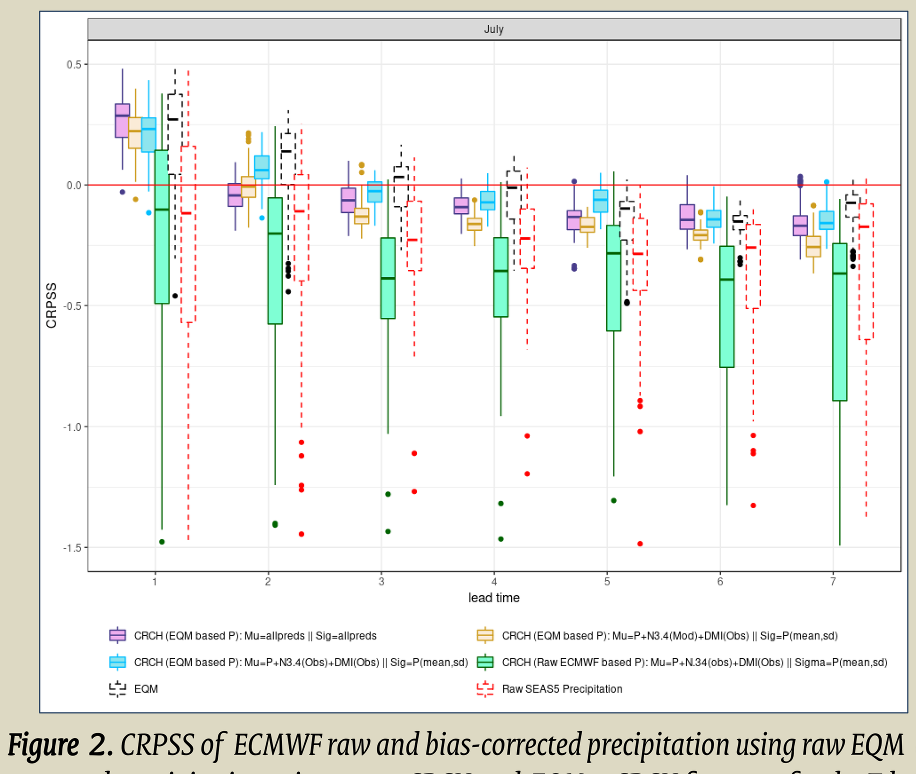

Figure 2. CRPSS of ECMWF raw and bias-corrected precipitation using raw EQM and post-processed precipitation using raw + CRCH and EQM + CRCH forecasts for the 7 lead months, verifying in July.

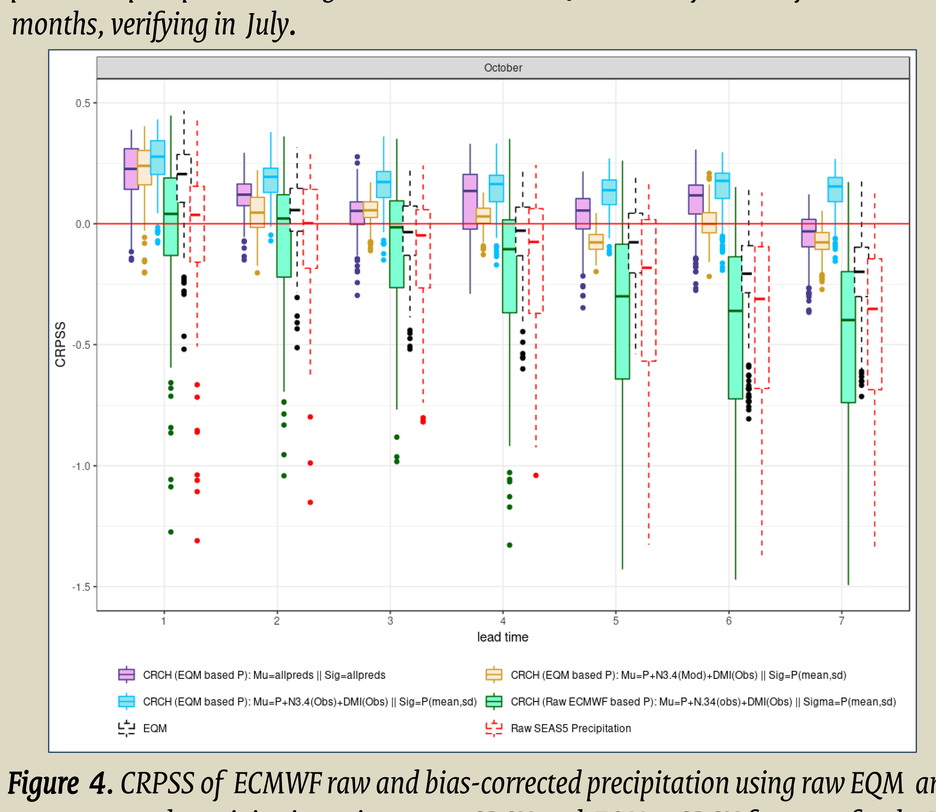

Figure 4. CRPSS of ECMWF raw and bias-corrected precipitation using raw EQM and post- processed precipitation using raw + CRCH and EQM + CRCH forecasts for the 7 lead months, verifying in October .

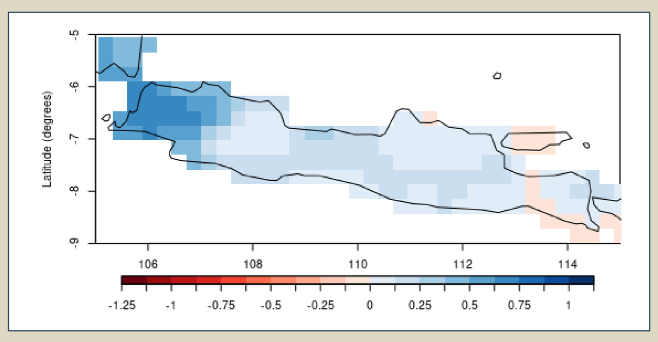

Figure 3. Map of CRPSS difference between CRCH (EQM based P): Mu=P+N3.4(Obs)+DMI || Sig=P(mean,sd) and EQM, verifying in July, lead time 1 month.

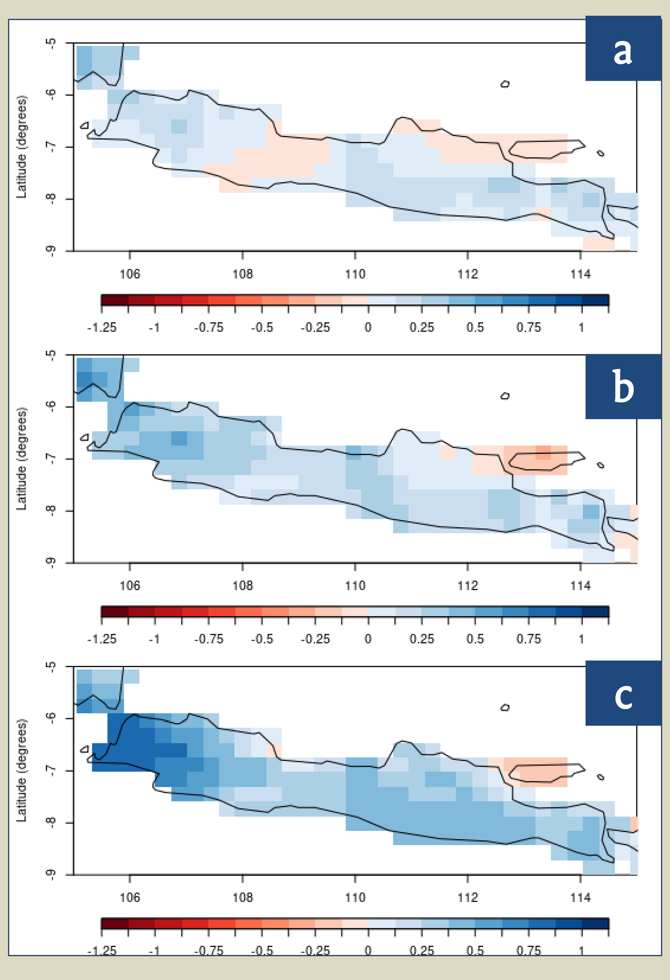

Figure 5 . Map of CRPSS difference between CRCH (EQM based P): Mu=P+N3.4(Obs)+DMI || Sig=P(mean,sd) and EQM, verifying in October, lead month +1 (a), +4 (b),and +7 (c) .

Figure 2 displays the CRPSS of ECMWF post-processed forecasts for the 7 lead months, verifying in July (dry month). It shows improved CRPSS after post-processing for lead month +1 using predictor set **b** and **d** (table 1), compared to EQM.

Figure 3 shows a map of CRPSS difference in July based on the predictor set **b** (table 1) in lead month +1.

Figure 4 displays the CRPSS of ECMWF post-processed forecasts for the 7 lead months, verifying in October (wet month). The improvement based on predictor set **b** (table 1) is clearly seen for all lead times . Predictor set d (table 1) also shows good but worse performance.

Figure 5 shows maps of CRPSS difference in October based on the predictor set **b** (table 1) for lead month +1 (a), lead time +4 (b), and lead time +7 (c). The longer lead times show more improvement of CRPSS, compared to EQM.

Using a subset of potential predictors in the fitting process shows more improvement compared to applying all potential predictors both for the location (μ) and the scale (σ).

Applying observed Nino 3.4 index as a predictor produces higher skill than applying the forecast Nino 3.4 index . We will analyze this further.

Improving the EQM-corrected precipitation forecast skill is still a challenge especially for the wet months December, January, February and March and the transition month April.

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